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Turning lights into flights: Estimating direct and indirect rebound effects for UK households

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Abstract

Energy efficiency improvements by households lead to *rebound effects* that offset the potential energy and emissions savings. Direct rebound effects result from increased demand for cheaper energy services, while *indirect* rebound effects result from increased demand for other goods and services that also require energy to provide. Research to date has focused upon the former, but both are important for climate change. This study estimates the combined direct and indirect rebound effects from seven measures that improve the energy efficiency of UK dwellings. The methodology is based upon estimates of the income elasticity and greenhouse gas (GHG) intensity of 16 categories of household goods and services, and allows for the embodied emissions of the energy efficiency measures themselves. Rebound effects are measured in GHG terms and relate to the adoption of these measures by an average UK household. The study finds that the rebound effects from these measures are typically in the range 5-15% and arise mostly from indirect effects. This is largely because expenditure on gas and electricity is more GHG-intensive than expenditure on other goods and services. However, the anticipated shift towards a low carbon electricity system in the UK may lead to much larger rebound effects.

Keywords: *Rebound effect; Sustainable consumption; Income effects; Re-spending*

1 Introduction

Global efforts to reduce greenhouse gas (GHG) emissions rely heavily upon improving energy efficiency in all sectors of the economy. For example, the ambitious '450 scenario', published by the International Energy Agency (IEA) anticipates energy efficiency delivering as much as 71% of the global reduction in carbon dioxide emissions in the period to 2020, and 48% in the period to 2035 (IEA, 2010). The technical and economic opportunities to improve energy efficiency are particularly large in the built environment which is consequently the target of multiple policy interventions. But the energy and GHG savings from such improvements may frequently be less than simple engineering estimates suggest as a consequence of various *rebound effects.* If these effects are significant, scenarios that ignore them are likely to be flawed and to provide misleading guidance for policymakers. But despite a growing body of evidence on the nature and importance of rebound effects (Sorrell, 2007), they continue to be overlooked by the majority of governments, as well as by international organisations such as the IEA.

This study seeks to estimate the magnitude of rebound effects following a number of energy efficiency improvements by UK households. We focus upon measures that improve the efficiency of heating and lighting systems and we estimate rebound effects in terms of their effect on global greenhouse gas (GHG) emissions. We extend the existing literature by accurately quantifying both 'direct' and 'indirect' rebound effects, and by also allowing for the emissions 'embodied' in energy efficiency equipment such as insulation materials.

The following section provides a classification of rebound effects for households and an overview of the relevant empirical literature. Section 3 summarises our approach, Section 4 describes the methodology in more detail and Section 5 introduces the analytical tools employed. Section 6 summarises our specific assumptions and examines their implications for estimates of rebound effects. Section 0 presents our results and investigates the sensitivity of those results to selected assumptions. Section 8 concludes.

2 Classifying and estimating rebound effects for households

‘Rebound effects’ is an umbrella term for a variety of behavioural responses to improved energy efficiency. The net result of these effects is typically to increase energy consumption and carbon/GHG emissions relative to a counterfactual baseline in which these responses do not occur. As a result, the energy and emissions ‘saved’ by the energy efficiency improvement may be less than anticipated.

Rebound effects for households have been classified in a number of different ways. To clarify, we introduce five distinctions.

2.1 Direct versus indirect rebound effects

For households, rebound effects are commonly labelled as either direct or indirect. *Direct* rebound effects derive from increased consumption of the, now cheaper, energy services such as heating, lighting or car travel. For example, the replacement of traditional light-bulbs with compact fluorescents will make lighting cheaper, so people may choose to use higher levels of illumination or to not switch lights off in unoccupied rooms. In contrast, *indirect* rebound effects derive from increased consumption of *other* goods and services (e.g. leisure, clothing) that also require energy and GHG emissions to provide. For example, the cost savings from more energy efficient lighting may be put towards an overseas holiday. As Figure 1 illustrates, this type of behaviour can be deliberately encouraged!

Figure 1 Encouragement of rebound effects

2.2 Energy versus emission rebound effects

Both direct and indirect rebound effects may be estimated in terms of energy consumption, carbon emissions or GHG emissions, but the magnitude of those effects will differ in each case. As the average carbon/GHG intensity of energy systems change, the relative magnitude of these rebound effects will also change – and in some circumstances, rebound effects may be found to be large in energy terms but small in GHG terms, or vice versa. The estimated magnitude of energy rebound effects will also depend upon how different energy carriers are aggregated – for example, on a thermal equivalent basis or weighted by relative prices (Cleveland et al., 2000).

2.3 Efficiency versus sufficiency rebound effects

Rebound effects do not result solely from cost-effective energy efficiency improvements, such as purchasing energy-efficient light bulbs, but also from energy-saving behavioural changes, such turning lights off in unoccupied rooms. These are sometimes referred to as 'sufficiency' rather than efficiency actions (Alcott, 2008; Druckman et al., 2011). But while efficiency improvements will lead to both direct and indirect rebound effects, sufficiency actions will only lead to indirect effects.

2.4 Direct versus embodied energy use and emissions

Households consume significant amounts of energy 'directly' in the form of heating fuels, electricity and fuels for private cars. But they also consume energy 'indirectly', since energy is used at each stage of the supply chain for all goods and services. For example, energy will be used to manufacture laptops in China, ship them to the UK and distribute them by road to retail outlets. This life-cycle energy use is commonly termed *embodied energy* while the associated emissions are termed *embodied emissions*. For OECD households, embodied GHG emissions frequently exceed the direct emissions associated with consumption of electricity and fuels. All of these emissions contribute to climate change, but only a portion occur within national boundaries and hence are covered by national targets on GHG emissions.

While direct rebound effects only affect direct energy use and emissions by the household, indirect rebound effects affect *both* direct and embodied energy use and emissions. For example, the savings from an energy-efficient heating system may be spent upon more heating (direct rebound, direct emissions), more lighting (indirect rebound, direct emissions) or more furniture (indirect rebound, embodied emissions).

2.5 Income versus substitution effects

As described in Annex I, both direct and indirect rebound effects may theoretically be decomposed into *income* and *substitution* effects. By making energy services cheaper, energy efficiency improvements increase the real income of households, thereby permitting increased consumption of all goods and services and increased 'utility' or consumer satisfaction. These adjustments are termed *income effects*. But since energy services are now cheaper relative to other goods and services, households may shift their consumption patterns *even if* their real income and hence utility was held constant. These adjustments are termed *substitution effects*. The change in consumption for a particular good or service is given by the sum of income and substitution effects for that good or service. The corresponding change in energy use or emissions may be estimated by multiplying the change in consumption by the energy/emission intensity of that good or service. The direct rebound effect represents the net result of the income and substitution effects for the relevant energy service, while the indirect rebound effect represents the net result of income and substitution effects for all the other goods and services purchased by the household - including other energy services.

Since the income and substitution effects for any individual good or service may be either positive or negative, the sum of the two may be either positive or negative. The consumption of any individual good or service may therefore increase or decrease following the energy efficiency improvement, and thereby either add to or reduce the household's aggregate energy use and GHG emissions.

A stylised example may make this clearer. Suppose a UK household replaces their car with a more fuel efficient model. Since the fuel costs for driving a given distance are now less, they may choose to spend some of the money saved on increased leisure driving at weekends (positive income effect for car travel). Similarly, since the cost of car travel has fallen relative to the cost of public transport, they may decide to travel to work by car rather than by train (positive substitution effect for car travel, negative substitution effect for public transport). At the same time, they may put some of the savings on gasoline expenditures towards a weekend Eurostar trip to Paris (positive income effect for public transport). The net effect on aggregate energy use and GHG emissions for the household will depend upon *both* the change in consumption of each individual good and service *and* the energy/GHG intensity of those goods and services.

2.6 Quantifying direct and indirect rebound effects for households

Table 1 uses the above categories to classify the limited number of studies that estimate both direct and indirect rebound effects for households. The table also indicates the number of categories used to classify household goods and services in each study.

The studies listed in Table 1 typically combine estimates of the energy consumption and/or emissions associated with different categories of household goods and services, with estimates of how the share of expenditure on these goods and services varies as a function of prices, income and other variables (Sorrell, 2010). The former are derived from a combination of Environmentally-Extended Input-Output models and Life Cycle Analysis (LCA), while the latter are derived from the econometric analysis of survey data on household expenditure. As indicated in Table 1, existing studies vary widely in the types of rebound effect covered, the categories used for classifying household expenditures and the types of actions investigated. While most focus upon improving energy efficiency in electricity, heating or personal travel, others examine sufficiency actions in those areas, such as reducing car travel, or broader actions such as reducing food waste. Rebound effects have been estimated in energy, carbon and GHG terms, but no study estimates and compares all three. Most studies use income elasticities to simulate the re-spending of cost savings on different goods and services and consequently capture the income effects of the energy efficiency improvement but not the substitution effects (for both direct and indirect rebound effects). While this may appear a drawback, the approach has advantage of being methodologically straightforward, avoiding the imposition of arbitrary restrictions on consumer behaviour (e.g. seperability) and allowing the use of relatively high levels of commodity disaggregation (Sorrell, 2010).

In this study, we estimate the direct and indirect rebound effects following improvements in the efficiency of heating and lighting systems in UK households. We estimate rebound effects in GHG terms and focus solely upon income effects, but extend the existing literature by also allowing for the emissions embodied in energy efficiency equipment, such as insulation materials.

Table 1: Previous estimates of combined direct and indirect rebound effects for households

Author	Number of Commodity Groups	Abatement action	Area	Measure	Effects captured	Energy/ emissions	Estimated rebound effect (%)
Lenzen and Day (2002)	150	Efficiency and behavioural change	Food; heating	GHGs	Income	Direct and indirect	45-123%
Alfreddson (2004)	300	Behavioural change	Food; travel; utilities	Carbon	Income	Direct and indirect	7-300%
Brannlund (2007)	13	Efficiency	Transport; utilities	Carbon	Income and substitution	Direct and indirect	120-175%
Mizobuchi (2008)	13	Efficiency	Transport; utilities	Energy	Income and substitution	Direct and indirect	12-38%
Kratena and Wuger (2008)	6	Efficiency	Transport; heating; electricity	Energy	Income and substitution	Direct only	37-86%
Druckman	16	Behavioural	Transport,	GHGs	Income	Direct and	7-51%

et al (2011)		change	heating, food			indirect	
Thomas (2011)	74	Efficiency	Transport, electricity	GHGs	Income	Direct and indirect	7-25%
Murray (2011)	36	Efficiency & sufficiency	Transport, lighting	GHGs	Income	Direct and indirect	5–40%

Note: 'Effects captured' refers to the modelling of both direct and indirect rebound effects.

3 Methodology - overview

This study focuses upon seven measures that a typical UK household could take to reduce their consumption of electricity or heating fuels, together with their associated greenhouse gas (GHG) emissions (Table 2). Four of these measures represent ‘dedicated’ energy efficiency investments, one represents the ‘natural replacement’ of energy conversion equipment with a more energy efficient option and two represent the ‘premature replacement’ of such equipment.[1] In 2009, we estimate that all but one[2] of the selected measures were likely to be cost effective for an average UK dwelling, although individual measures are not suitable for all dwellings and the potential cost savings vary widely from one dwelling to another. Between 2008 and 2012, four of the measures were eligible for investment subsidies under the UK Carbon Emissions Reduction Target (CERT). These subsidies are provided by energy suppliers and are funded through a levy on household energy bills, with their availability varying with the socio-economic circumstances of the household (DECC, 2010e).

Table 2: Selected energy efficient measures

No.	Measure	Type	Target	Eligible for subsidy?
1	Cavity wall insulation in un-insulated cavities	Dedicated	Heating	Yes
2	Topping up loft insulation to 270 mm	Dedicated	Heating	Yes
3	Replacing existing boilers with condensing boilers	Natural replacement	Heating	No
4	Insulating hot water tanks to best practice (75 mm jacket)	Dedicated	Heating	Yes
5	Replacing existing incandescent bulbs with compact fluorescents (CFLs)	Premature replacement	Electricity	No
6	Replacing all existing lighting with LEDs	Premature replacement	Electricity	Yes
7	Solar thermal heating	Dedicated	Heating	Yes

In what follows, we estimate the impact on global GHG emissions of all *eligible* English dwellings adopting the relevant measure - for example, installing cavity wall insulation in all dwellings with unfilled cavity walls. The estimated impacts are the net result of three different effects which we term as the *engineering*, *embodied* and *income effects* respectively:

- *Engineering effect* (ΔH): Each measure is expected to reduce the amount of energy required to deliver a given level of energy service (e.g. heating, lighting) over its lifetime. If consumption of energy services were to remain unchanged, there would be a corresponding reduction in household electricity and/or fuel use and the associated GHG emissions. Hence, in this paper the *engineering effect* is an estimate of the change in direct GHG emissions for a given energy service assuming that consumption of that energy service remains unchanged.

- *Embodied effect (ΔM):* The manufacture and installation of the relevant energy efficient equipment (e.g. insulation materials) is associated with GHG emissions at different stages of the supply chain. The *embodied effect* is an estimate of the additional impact on global GHG emissions of adopting the energy efficiency measure compared to the relevant alternative. The alternative may be doing nothing in case of dedicated measures, purchasing less energy efficient equipment in case of natural replacement or continuing to use existing equipment in case of premature replacement.

- *Income effect (ΔG):* The reduction in the effective price of the energy service is equivalent to an increase in real household income. This allows households to consume more goods and services and thereby increase their overall 'utility'. The *income effect* is an estimate of the impact on global GHG emissions of this increased consumption of goods and services, including energy services. The income effect includes both direct emissions from the consumption of energy by the household and embodied emissions from consumption of non-energy goods and services. Emissions from electricity consumption are commonly labelled as direct, although they occur at the power station.

The estimated total impact (ΔQ) of the energy efficiency measure on global GHG emissions is given by:

$$\Delta Q = \Delta H + \Delta M + \Delta G \tag{1}$$

For each measure, we expect the engineering effect (ΔH) to be negative and the income effect (ΔG) to be positive. We expect the embodied effect (ΔM) to be positive for dedicated measures, since the counterfactual involves no investment. But the sign of this effect is ambiguous for natural and premature replacement measures since the counterfactual involves investment in inefficient equipment. Overall, we expect each measure to reduce global GHG emissions, but by less than simple engineering calculations suggest ($\left|\Delta Q\right| \leq \left|\Delta H\right|$). However, if the embodied and income effects exceed the engineering effect, the measure will *increase* global GHG emissions ('backfire')

The rebound effect (*RE*) from the energy efficiency improvement may then be defined as:

$$RE = \frac{(Expected\ savings - Actual\ savings)}{Expected\ savings} = \frac{\Delta H - \Delta Q}{\Delta H} \tag{2}$$

Or:

$$RE = -\left[\frac{\Delta G + \Delta M}{\Delta H}\right] \tag{3}$$

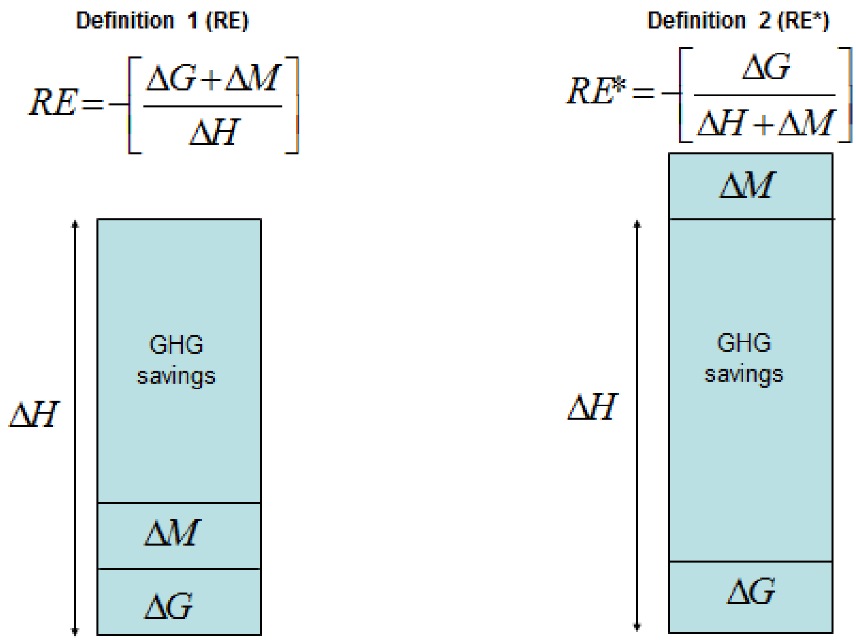
This definition (illustrated in Figure 2) treats the embodied effect (ΔM) as offsetting some of the anticipated GHG savings from the measure (ΔH) and thereby contributing to the rebound effect. An alternative approach is to subtract the embodied effect from the anticipated GHG savings:

$$RE^* = -\left[\frac{\Delta G}{(\Delta H + \Delta M)}\right] \tag{4}$$

The difference between the two measures will depend upon the size of the embodied effect relative to the engineering and income effects.

As defined here, the income effect (ΔG) derives from both increased consumption of energy by the household (including the energy commodity that benefits from the energy efficiency improvement) and increased consumption of other goods and services (e.g. clothing, education). It therefore combines the income component of both the direct and indirect rebound effect and relates to both direct and embodied emissions. However, it does not provide a fully accurate measure of direct and indirect rebound effects because substitution effects are ignored.

Figure 2 Two definitions of the rebound effect



4 Methodology - details

Each measure is assumed to be installed in all eligible dwellings in the UK in 2009 (t=1). We estimate the impact on GHG emissions over a period of T years (t=1 to T) where T is less than the economic lifetime of each measure. For simplicity, we present, all our results for a ten-year period (T=10) and hold most of the variables affecting GHG emissions fixed over this period (e.g. household income, commodity prices, number of dwellings etc.). However, the framework can also allow these variables to change over time. We take 2005 as the reference year for all real values.

Our approach can be broken down into four stages, as follows.

4.1 Estimating the engineering effect

We use an engineering model (Firth et al., 2009) to estimate the direct energy consumption of the English dwelling stock by year (t=1 to T) and energy carrier (f). The relevant energy carriers are gas, oil, solid fuels and electricity. Dividing by the total number of English dwellings gives the average direct energy consumption per-household (E_{ft}). We then apply the relevant energy efficiency measure to all *eligible* dwellings (which may be a subset of the total) and re-estimate the average per-household direct energy consumption (E'_{ft}) assuming the demand for energy services remains unchanged. The change in average annual per-household direct energy consumption as a result of the measure is then:

$$\Delta E_{ft} = E'_{ft} - E_{ft} \qquad (5)$$

These energy savings are assumed to begin in the year of installation of the relevant measure (t=1). With this approach, the estimated energy savings are averaged over the entire housing stock but only a portion of dwellings may be eligible for and hence benefiting from the relevant measure. For example, some dwellings do not have cavity walls while others have cavity walls that are already filled, so only a proportion of dwellings are suitable for cavity wall insulation. This means that, in percentage terms, the estimated average energy savings may be <u>less</u> than would be obtained for an individual dwelling installing the relevant measure, but they are representative of the potential energy savings obtainable from installing these measures in the English housing stock as a whole.[3]

We then use data on the GHG intensity of each energy carrier (s_{ft} in $kgCO_{2e}/kWh$) to estimate the average per-household change in direct GHG emissions assuming the demand for energy services remains unchanged. We term this the ***engineering effect*** of the energy efficiency improvement (ΔH_t):

$$\Delta H_t = \sum_f s_{ft} \Delta E_{ft} \tag{6}$$

4.2 Estimating the embodied effect

We use the results of a number of life cycle analysis (LCA) studies to estimate the GHG emissions that are incurred in manufacturing and supplying the relevant energy efficient equipment and installing it in all eligible dwellings. We assign these embodied emissions to the year in which the measures are installed and divide by the total number of dwellings to give the average per-household embodied emissions for the relevant measure (M'_t). If T is less than the economic lifetime of the energy efficiency measure, the embodied emissions will only be relevant for the base year (i.e. $M'_t = 0$ for t>1).

We also estimate the average per-household embodied emissions of the relevant alternative (M_t). If this alternative has an economic lifetime that is less than T, the measure will avoid the purchase of conversion equipment in subsequent years, with the result that the embodied emissions associated with those purchases are also avoided (i.e. $M_t > 0$ for some t>1). This is the case, for example, with conventional lighting which has a shorter lifetime than energy efficient lighting.

The difference between these two estimates represents the *incremental* embodied emissions associated with the energy efficiency measure. We term this the ***embodied effect*** of the energy efficiency improvement (ΔM_t):

$$\Delta M_t = M'_t - M_t \tag{7}$$

4.3 Estimating the income effect

In the UK, household energy bills normally include a fixed annual charge (a_{ft} in £/dwelling/year) and a charge per unit of energy used (k_{ft} in £/kWh). Energy efficiency improvements only affect the latter. We use data for 'average' English dwelling in terms of energy consumption to estimate the change in average annual energy expenditures following the adoption of each measure (ΔC_t), assuming the demand for energy services remains unchanged:

$$\Delta C_t = \sum_f k_{ft} \Delta E_{ft} \tag{8}$$

We also estimate the capital cost associated with installing the measure in all eligible dwellings and divide by the total number of dwellings to give the average per-household capital cost (K'_t). We do the same for the relevant alternative (K_t), with the difference between the two representing the *incremental* capital cost of each measure (ΔK_t):

$$\Delta K_t = K'_t - K_t \tag{9}$$

We assume that the full capital costs are incurred in the year in which the measure is installed (i.e. $K'_t = 0$ for t>1).[4] Again, if the relevant alternative has an economic lifetime that is less than *T,* the measure avoids equipment purchases in subsequent years (i.e. $K_t > 0$ for some t>1). For simplicity, we do not discount these avoided capital costs.

We now look at how these costs affect the average annual real disposable income for a household (Y_t). We treat the sum of the change in energy expenditures and the net capital payments in a given year as analogous to a change in real disposable income (ΔY_t):

$$\Delta Y_t = -(\Delta C_t + \Delta K_t) \tag{10}$$

Households are assumed to divide their disposable income between their expenditure on goods and services (X_t) and saving (S_t). For simplicity, we assume that households save a fixed fraction (r)[5] of their disposable income each year:

$$\Delta S_t = r\,\Delta Y_t \tag{11}$$

We assume that the remainder is entirely distributed between expenditure on different categories of goods and services – including electricity and fuels. Letting X_{it} represent expenditure on commodity group i (i=1 to I), then:

$$\Delta X_t = \sum_{i=1}^{I} \Delta X_{it} = (1-r)\Delta Y_t \tag{12}$$

From consumer demand theory, this 'adding up restriction' leads to the so-called 'Engel aggregation condition', as follows (Deaton and Muelbauer, 1980):

$$\sum_{i=1}^{I} \beta_i X_{it} = (1-r)Y_t \tag{13}$$

Where β_i represents the income elasticity of expenditure for commodity group i:

$$\beta_i = \frac{\Delta X_{it}}{\Delta Y_t}\frac{Y_t}{X_{it}} \tag{14}$$

Changes in expenditure on electricity and fuels will lead to changes in direct emissions while changes in expenditure on other goods and services will lead to changes in embodied emissions. Savings are treated here as a source of funds for capital investment in the UK which will also be associated with GHG emissions.[6] Hence, changes in expenditure and savings in a given year will lead to changes in GHG emissions which may either reinforce or offset the 'engineering' savings in GHG emissions. Letting u_{it} represent the GHG intensity of expenditure in category i and u_{st} represent the GHG intensity of UK investment[7] (both in $kgCO_2e/£$), the average per-household change in GHG emissions as a consequence of the change in real disposable income is given by:

$$\Delta G_t = \sum_{i=1}^{I} [u_{it} \Delta X_{it}] + u_{st} r \Delta Y_t \tag{15}$$

Using Equation 14, the change in expenditure for each category (i) in year t can be written as:

$$\Delta X_{it} = \beta_i \frac{\Delta Y_t}{Y_t} X_{it} \tag{16}$$

Substituting ΔX_{it} from Equation 16 into Equation 15:

$$\Delta G_t = \left[\frac{\Delta Y_t}{Y_t} \right] \sum_{i=1}^{I} [u_{it} \beta_i X_{it}] + u_{st} r \Delta Y_t \tag{17}$$

Substituting for Y_t from Equation 13, this can also be written as:

$$\Delta G_t = \Delta Y_t \left[\frac{(1 - r_t)}{\sum_{i=1}^{I} \beta_i X_{it}} \sum_{i=1}^{I} [u_{it} \beta_i X_{it}] + u_{st} r \right] \tag{18}$$

We term ΔG_t the ***income effect*** of the energy efficiency improvement.

4.4 Estimating the rebound effect

Combining Equations 3 and 18, the rebound effect averaged over a period of T can then be estimated from:

$$RE = -\frac{\sum_{t=1}^{T}\left\{\Delta Y_t\left(\frac{(1-r_t)}{\sum_{i=1}^{I}\beta_i X_{it}}\sum_{i=1}^{I}\left[u_{it}\beta_i X_{it}\right]+u_{st}r\right)+\Delta M_t\right\}}{\sum_{t=1}^{T}\Delta H_t} \tag{19}$$

5 Analytical tools

To develop the above estimates, we combine results from three separate analytical models. The *Community Domestic Energy Model* (CDEM) is used to estimate the energy savings from applying a number of standard energy efficiency measures to UK dwellings; the *Econometric Lifestyle Environmental Scenario Analysis* (ELESA) model is used to estimate how these cost savings are spent on different categories of household goods and services; and the *Surrey Environmental Lifestyle Mapping Framework* (SELMA) is used to estimate the global GHG emissions from the production, distribution and consumption of those categories of goods and services, together with household savings. These three models are briefly described below.

5.1 Community Domestic Energy Model (CDEM)

The CDEM model has been developed by Firth *et al* (2009) at Loughborough University to simulate energy use in the English housing stock and to explore options for reducing CO_2 emissions. The CDEM is one of a family of bottom-up, engineering models of the English housing stock that are based upon algorithms originally developed by the UK Building

Research Establishment (Kavgic et al.; Shorrock and Dunster, 1997). The CDEM consists of two main components: a 'house archetype calculation engine' and a core 'building energy model'. The archetype calculation engine defines the characteristics of 47 individual house archetypes, which are used to represent all the dwelling types in the English housing stock.[8] The archetypes are defined by different combinations of built form and age (Table 3), since these variables have a dominant influence on heat loss and hence the energy use for space heating - the former via average floor area and the number of exposed walls and the latter by the thermal standards of construction.

Table 3: House archetype categories in the Community Domestic Energy Model

Built form categories	**Dwelling age band categories**
End terrace	pre-1850; 1851-1899; 1900-1918; 1919-1944; 1945-1964; 1965-1974; 1975-1980; 1980-1990; 1991-2001
Mid-terrace	
Semi-detached	
Detached	
Flat: purpose-built	1900-1980; 1919-1944; 1945-1964; 1965-1974; 1975-1980; 1980-1990; 1991-2001
Flat: converted or other	pre-1850; 1851-1899; 1900-1918; 1990-1944

Note: Pre-1900 purpose-built flats and post-1945 other flats were not considered as these combinations occur very infrequently in the housing stock.

Model input parameters are defined for each archetype, related to location, geometry, construction, services and occupancy. The model then estimates the solar gains, internal heat gains and dwelling heat loss coefficient[9] for each archetype and calculates energy consumption by energy type (solid, gas, liquid and electricity) and end-use (space heating, hot water, cooking, lights and appliances) under specified weather conditions. Estimates of the energy consumption in an average dwelling in a given year (E_{ft}) can then be derived from:

$$E_{ft} = \frac{\sum_{at} \left[N_{at} E_{fat} \right]}{\sum_{a} N_{at}} \qquad (20)$$

Where E_{fat} represents the estimated consumption of energy carrier f in archetype a in year t, and N_{at} represents the estimated number of dwellings of that archetype in the English housing stock in that year. We take these estimates, which refer to an average English dwelling, as representative of the energy consumption of an average UK dwelling.

5.2 Econometric Lifestyle Environmental Scenario Analysis model (ELESA)

ELESA is a Structural Time Series Model (STSM) (Harvey, 1989) for UK household expenditure developed by Chitnis *et al* (2012; 2009) at the University of Surrey. It is estimated from quarterly time series data on aggregate UK household consumption expenditure over the period 1964-2009. The model estimates the expenditure on 16 different categories of goods and services (Table 4) as a function of household income, prices, temperature (where relevant) and a stochastic (rather than a deterministic) time trend (Hunt and Ninomiya, 2003). The stochastic trend aims to capture the aggregate effect of underlying factors such as technical progress, changes in consumer preferences, socio-demographic factors and changing lifestyles which are difficult to measure (Chitnis and Hunt, 2009; Chitnis and Hunt, 2010a, b). ELESA is used to forecast future household expenditure and associated GHG emissions under different assumptions for the relevant variables.

In this study, estimates of the long-run income elasticity (β_i) for each category are obtained from ELESA and used within Equation 18 to estimate the income effect.[10] These elasticities, together with household expenditure are held fixed over the projection interval.

Table 4: Commodity categories

Category (*i*)	CCOIP category	Description
1	1	Food & non-alcoholic beverages
2	2	Alcoholic beverages, tobacco, narcotics
3	3	Clothing & footwear
4	4.5.1	Electricity
5	4.5.2	Gas
6	4.5.3 and 4.5.4	Other fuels
7	4.1 to 4.4	Other housing
8	5	Furnishings, household equipment & household maintenance
9	6	Health
10	7.2.2.2	Vehicle fuels and lubricants
11	Rest of 7	Other transport
12	8	Communication
13	9	Recreation & culture
14	10	Education
15	11	Restaurants & hotels
16	12	Miscellaneous goods & services

Notes: COICOP - Classification of Individual Consumption According to Purpose. 'Other housing' includes rent, mortgage payments, maintenance, repair and water supply. Other transport includes non-fuel expenditure on private vehicles.

5.3 Surrey Environmental Lifestyle Mapping framework (SELMA)

The SELMA model has been developed by Druckman *et al* (2008) at the University of Surrey to estimate the GHG emissions that arise in the production, distribution, consumption and disposal of goods and services purchased in the UK.[11] This is known as emissions accounting from the 'consumption perspective' (Druckman et al., 2008; Druckman and Jackson, 2009a, c, d; Minx et al., 2009; Wiedmann et al., 2007; Wiedmann et al., 2006). The estimates include emissions from direct energy use, such as for personal transportation and space heating, as well as embodied emissions[12] from the production and distribution of goods and services. An important feature of SELMA is that it takes account of all emissions incurred as a result of final consumption, whether they occur in the UK or abroad. To do this, the estimation of the embodied emissions is carried out using a Quasi-Multi Regional Environmentally-Extended Input-Output sub-model (Druckman and Jackson, 2008).

For this study, emissions due to household expenditure are classified into 16 categories (Table 4) following the rationale outlined in Druckman and Jackson (2009b). The GHG intensity of expenditure (in kgCO_2e/£) in each of these categories (u_{it}) is derived by dividing the estimated GHG emissions associated with UK consumption of those goods and services by the real expenditure of UK households on those goods and services. Both the emissions and real expenditure data refer to 2004. We also use the GHG intensity of UK investment in 2004 as a proxy for the GHG intensity of household savings. These estimated GHG intensities are then held fixed over the projection interval.

6 Assumptions and estimated effects

In this section, we summarise our underlying assumptions and resulting estimates for the engineering effect (ΔH_t), embodied effect (ΔM_t) and income effect (ΔG_t) respectively. The estimates are presented for each measure individually, as well as for two combinations of measures and are averaged over a period of ten years (T=10). The estimates relate to an 'average' dwelling, although only a portion of dwellings may be eligible for and hence benefiting from the relevant measure.

Some relevant assumptions from the CDEM are summarised in Table 5, while the associated assumptions for the GHG intensity of delivered energy (in $kgCO_{2e}$/kWh) and the standing and unit cost of the energy carriers are given in Table 6. Note that we assume a constant proportion of low energy lighting and a constant thickness of tank insulation (29.4mm) across all dwellings, although in practice many dwellings do not have hot water tanks and the proportion of low-energy lighting varies widely.

Table 5: Some relevant assumptions from the CDM model for 2009

Total number of English dwellings	21,262,825
Proportion of dwellings eligible for cavity wall insulation	39.4%
Proportion of dwellings eligible for topping up loft insulation	67.9%
Proportion of dwellings eligible for condensing boilers	80%
Proportion of dwellings eligible for CFLs, LEDs and tank insulation	100%
Mean net wall area of dwellings eligible for cavity wall insulation	67.3 m^2
Mean roof floor area of dwellings eligible for loft insulation	45 m^2
Mean thickness of existing loft insulation in dwellings eligible for loft insulation	149 mm
Proportion of households with non-condensing boilers	80%
Mean thickness of existing hot water tank insulation	29.4 mm
Proportion of current light bulb stock that are compact fluorescents	40%
Average number of light fittings per-house	24

Table 6: GHG intensity and cost of energy carriers for an average UK household in 2009

	GHG intensity ($kgCO2_e/kWh$)	Standing costs (£/year)	Unit costs (£/kWh)
Gas	0.22554	£93.92	£0.03
Oil	0.30786	-	£0.05
Solid	0.41342	-	£0.04
Electricity	0.61707	£44.51	£0.11

Sources: (Coals2U, 2011; DECC, 2010a, b; Hansard, 2011)

Notes:

- Nominal costs for a UK household with 'average' energy consumption. Costs for gas and electricity represent a weighted average of credit, direct debit and prepayment customers.

As indicated in Table 7, we estimate that an average English household consumed approximately 22.5MWh of electricity and fuels in 2009 at a total cost of ~£1100, of which 90% was consumption related (unit costs) and the remainder standing charges. This energy consumption was associated with approximately 7.1 tonnes of direct GHG emissions. Electricity accounted for 20% of direct energy consumption, 39% of energy-related GHG emissions and 45% of energy expenditures. Gas provided the dominant fuel for space and water heating, accounting for 90% of total fuel consumption and 72% of total energy consumption. Solid fuels provided a small and declining contribution, accounting for only 4% of energy use in 2009 and 5% of GHG emissions. We take these estimates as representative of UK households as a whole.

Table 7: Estimated annual energy consumption, energy expenditure and energy-related GHG emissions for an 'average' UK dwelling in 2009

	Gas	Electricity	Oil	Solid	Total fuel	Total energy
Consumption (kWh)	16237	4415	1101	787	18125	22540
Expenditure (£)	509	499	58	32	600	1099
GHG emissions ($kgCO_{2e}$)	3662	2724	339	325	4326	7051

Note: Expenditures in nominal terms. Total fuel is the sum of gas, oil and solids. Total energy is total fuel plus electricity.

Estimates of the percentage annual energy (ΔE), cost (ΔC) and GHG (ΔH) savings from applying the measures all eligible dwellings are shown in Table 8. This also shows the estimated total impact of applying measures 1, 2, 3, 4 and 5 in combination, as well as measures 1, 2, 3, 4 and 6 in combination. Since the CDEM cannot be used to simulate solar thermal heating, we use a variety of sources to estimate the potential energy savings from fitting solar thermal panels to the estimated 40% of UK households with south facing roofs (see Annex 2). The results suggest that cavity wall insulation and upgrading to condensing boilers could each reduce energy-related GHG emissions by ~6%, installing solar thermal could reduce emissions by ~2.6%, and each of the remaining measures could reduce emissions by ~1.5%. In combination, the measures have the potential to reduce energy-related GHG emissions by ~16%, which corresponds to ~5% of total UK GHG emissions and ~4% of the 'GHG footprint' (i.e. total direct and embodied emissions) of an average UK household.[13]

Since energy-efficient lighting converts less of the input energy into unwanted heat, the energy and emission savings from this measure may be offset by increased consumption of heating fuels in order to maintain internal temperatures (the 'heat replacement effect'). Holding demand for energy services constant, we estimate that replacement of existing lighting by CFLs and LEDs will increase total household energy consumption by ~1%, but reduce energy costs by ~5% and energy-related GHG emissions by ~1.3%. Similarly, our estimates account for the reduction in the marginal energy savings from individual measures when used in combination with others.

Table 8: Estimated annual savings in energy consumption, energy costs and energy-related GHG emissions from applying the measures to an 'average' UK dwelling in 2009

No.	Measure	Annual energy saving (%)	Annual energy cost saving (%)	Annual GHG saving (%)	Ratio of cost to GHG savings
1	Cavity wall insulation	7.3	4.9	5.9	*0.83*
2	Loft insulation	1.9	1.3	1.5	*0.87*
3	Condensing boiler	8.4	4.7	5.9	*0.79*
4	Tank insulation	1.7	1.5	1.7	*0.88*
5	CFLs	0.1	1.4	1.2	*1.16*
6	LEDs	0.2	1.7	1.4	*1.22*
7	Solar thermal	3.1	2.6	2.5	*1.04*
8	1,2,3,4 and 5	18.5	13.2	15.6	*0.85*
9	1,2,3,4 and 6	18.5	13.5	15.8	*0.85*

Annex 3 summarises our assumptions and estimates for the embodied effect of each measure (ΔM). These are based upon LCA studies for the relevant materials and equipment, but this evidence is patchy and frequently makes inconsistent assumptions for key variables such as the GHG intensity of electricity. We assume that the incremental embodied emissions associated with the natural replacement of existing boilers are zero and we provide two sets of estimates for energy efficient lighting - the first allowing for the EU phase-out of incandescent bulbs in the period to 2016 and the second assuming that these bulbs continue to be available. In the latter case, installing energy efficient lighting allows consumers to avoid replacing incandescent bulbs at two-year intervals over the subsequent ten years (see Annex 1). Since the embodied emissions associated with these purchases are also avoided, the second scenario leads to a lower estimate of the incremental embodied emissions associated with energy efficient lighting.

Table 9 summarises our estimates for the incremental capital cost of each measure (ΔK) which are based upon information provided by the UK government (DECC, 2010d). Several of the measures are eligible for subsidies through CERT, with the level of subsidy being greater if the head of the house is at least 70 years old or is in receipt of certain income-related benefits. Approximately 11.2 million UK households (42%) fall into this so-called Priority Group (PG), and DECC (2010d) estimates that approximately 55% of CERT-subsidised measures will be installed in PG households. Hence, the estimates take into account both the level of subsidies available for PG and non-PG households and the relative proportion of installations expected within each. As with the embodied effect, we assume that the incremental capital cost of replacing an existing boiler with a condensing boiler is zero and we provide two sets of estimates for energy efficient lighting.

Table 9: Estimated incremental capital cost for an 'average' UK dwelling over a period of ten years

No.	Measure	Incremental capital cost – no subsidy (£)	Incremental capital cost - with subsidy (£)
1	Cavity wall insulation	179	41
2	Loft insulation	235	54
3	Condensing boiler	-	-
4	Tank insulation	17.50	6.3
5	CFLs	57.6 (-21.6)	57.6 (-21.6)
6	LEDs	254.4 (175.2)	127.2 (48)
7	Solar thermal	1489	532
8	1,2,3,4 and 5	409.9	79.7
9	1,2,3,4 and 6	256.3	53.3

Note: Estimates refer to an 'average dwelling' and are derived by estimating the capital costs associated with installing the measure in all eligible dwellings and dividing by the total number of dwellings. Estimates in brackets for energy efficient lighting are *without* allowing for the EU ban on incandescent bulbs.

Table 10 summarises our assumptions for the expenditure share (X_i / X), long-run income elasticity (β_i), GHG intensity of expenditure (u_i) and share of total household GHG emissions for each of the 16 categories of goods and services (see also Figure 3). Expenditure on domestic energy (i.e. gas, electricity and other fuels) accounted for 2.4% of household income in 2009, but this figure hides considerable variation between individual households. Approximately 4 million English households (18.4%) were estimated to be in 'fuel poverty' in 2009 - defined as needing to spend more than 10% of their income on energy in order to maintain an adequate standard of warmth (Hills, 2011).[14]

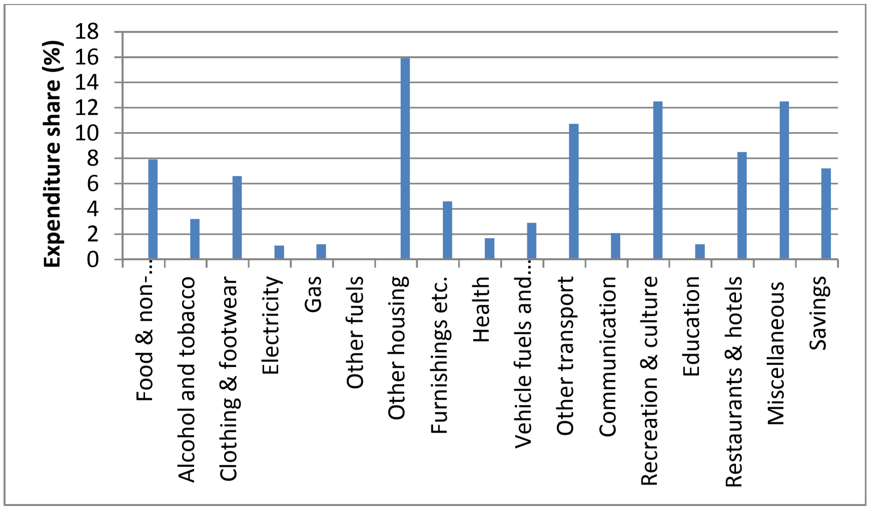
Figure 3 (panel 2) illustrates that the GHG intensity of expenditure (u_i) on electricity, gas and other fuels is approximately four times greater than the mean GHG intensity of expenditure on the other commodity groups and ten times greater than the share-weighted mean. But this high GHG intensity is offset by the relatively small share of energy in total expenditure (Figure 3, panel 1), with the result that domestic energy consumption accounts for less than one quarter of the GHG footprint of an average UK household (~28tCO_{2e}/year) (Druckman and Jackson, 2010). 'Other transport' accounts for around 16% of the total GHG footprint (Figure 3, panel 3), owing to the large contribution from aviation fuels, together with the emissions that are embodied in private cars and associated infrastructure. Aviation is estimated to account for ~5% of the total GHG emissions of an average UK household, despite the fact that up to half of UK households do not fly in an average year (Cairns et al., 2006). Moreover, allowing for the additional radiative forcing from contrails and nitrogen oxides could double this figure (Druckman and Jackson, 2010; RCEP, 2007). For car travel, the embodied emissions in vehicles and other infrastructure are only slightly less than the direct emissions from vehicle fuels which account for 9% of an average household's footprint (Figure 3, panel 3).

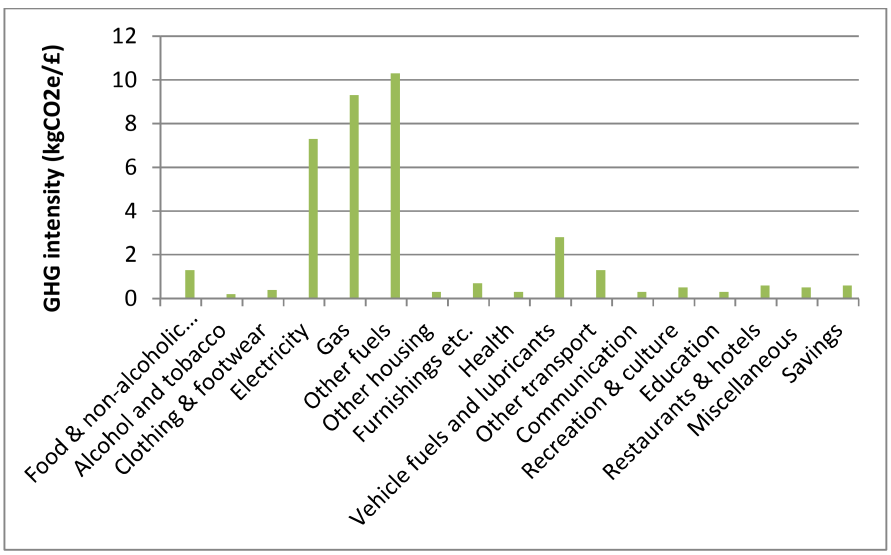
Table 10: Estimated expenditure shares, income elasticities and GHG intensities

No.	Description	Real expenditure share in 2009 (%) (X_i / X)	Long-run income elasticity (β_i)	GHG intensity ($kgCO_2e$/ £) (u_{it})	GHG intensity as % of gas	GHG emissions as % of total
1	Food & non-alcoholic beverages	7.9	0.18	1.3	14.0	11.7
2	Alcohol and tobacco	3.2	0.29	0.2	2.2	0.7
3	Clothing & footwear	6.6	0.36	0.4	4.3	3.0
4	Electricity	1.1	0.30	8.0	78.5	9.1
5	Gas	1.2	0.00	9.3	100.0	12.4
6	Other fuels	0.1	0.35	10.3	110.8	1.6
7	Other housing	15.8	0.15	0.3	3.2	5.4
9	Furnishings etc.	4.7	0.70	0.7	7.5	3.7
9	Health	1.7	0.08	0.3	3.2	0.6
10	Vehicle fuels and lubricants	2.9	0.08	2.8	30.1	9.2
11	Other transport	10.7	0.50	1.3	14.0	15.8
12	Communication	2.1	0.17	0.3	3.2	0.7
13	Recreation & culture	12.5	0.37	0.5	5.4	7.1
14	Education	1.2	-0.23	0.3	3.2	0.4
15	Restaurants & hotels	8.6	0.68	0.6	6.5	5.9
16	Miscellaneous	12.5	0.41	0.5	5.4	7.1
	Saving	7.8	0.0	0.6	6.5	5.3

Source: GHG intensity estimates from SELMA. Elasticity estimates from ELESA. Expenditure share estimates from the UK Office of National Statistics (ONS).

Figure 3 Expenditure shares, GHG intensities and share of total household GHG emissions by commodity group





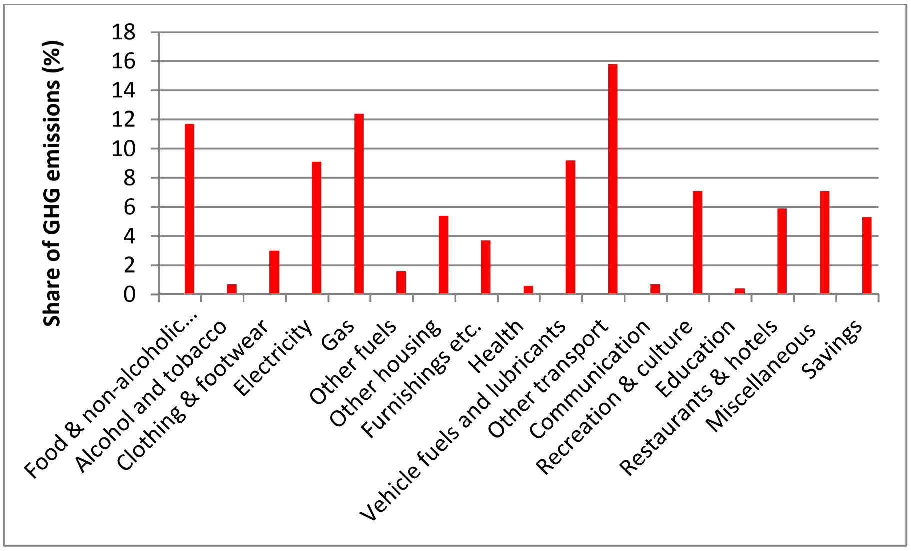

Share of GHG emissions (%)
18
16
14
12
10
8
6
4
2
0
Food & non-alcoholic...
Alcohol and tobacco
Clothing & footwear
Electricity
Gas
Other fuels
Other housing
Furnishings etc.
Health
Vehicle fuels and lubricants
Other transport
Communication
Recreation & culture
Education
Restaurants & hotels
Miscellaneous
Savings

Table 11 and Figure 4 summarise the resulting estimates for the engineering (ΔH), embodied (ΔM) and income (ΔG) effects for each of the measures, averaged over a ten year period. This demonstrates that, averaged across all measures, the embodied effect is around 40% of the income effect (or 15% if solar thermal is excluded), while the income effect is around 13% of the engineering effect. The implications of this for the estimated rebound effects (*RE*) are explored below.

The estimated contribution of each commodity group to the income effect (Figure 5) depends upon the product of its expenditure (X_i), GHG intensity of expenditure (u_i),and income elasticity (β_i). So for example, vehicle fuels are GHG intensive, but only account for 2.5% of the estimated income effect owing to their small share of total expenditure (2.1%) and low income elasticity (0.08). In contrast, other transport is only one third as GHG intensive as vehicle fuels, but accounts for 26% of the estimated income effect owing to its large expenditure share (11.5%), and high income elasticity (0.5). This suggests that our results could be sensitive to the elasticity estimates used – and in particular to our estimate of a zero income elasticity for gas.[15] We test the sensitivity of our results to this elasticity below.

Table 11: Estimated engineering, embodied and income effect from each measure for an 'average' dwelling over a ten year period (percentage of baseline GHG emissions)

No.	Measure	Engineering effect (ΔH)	Embodied effect (ΔM)	Income effect (ΔG)
1	Cavity wall insulation	-8.8	0.13	1.10
2	Loft insulation	-2.3	0.27	0.29
3	Condensing boiler	-9.0	0.00	1.16
4	Tank insulation	-2.6	0.01	0.33
5	CFLs	-2.1	0.03	0.28
6	LEDs	-2.5	0.08	0.33
7	Solar thermal	-3.8	0.99	0.48
8	1,2,3,4 and 5	-23.8	0.41	3.01
9	1,2,3,4 and 6	-24.2	0.46	3.07

Note: Estimates refer to an 'average dwelling' and are derived by estimating the total effect associated with installing the measure in all eligible dwellings and dividing by the total number of dwellings.

Figure 4 Estimated engineering, embodied and income effect from each measure for an 'average' dwelling over a ten year period (%)

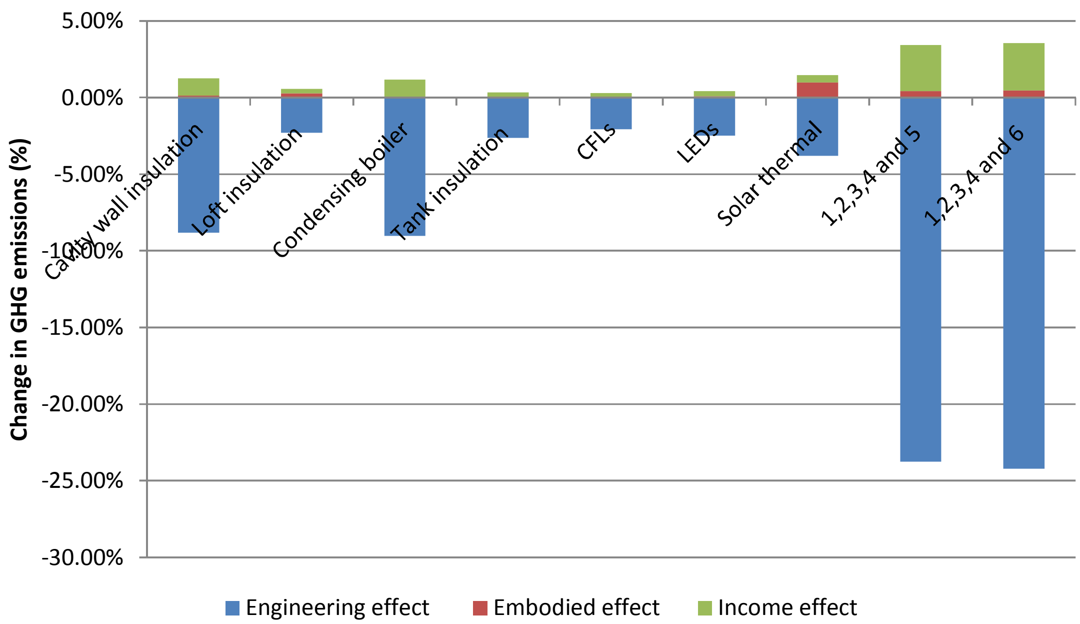
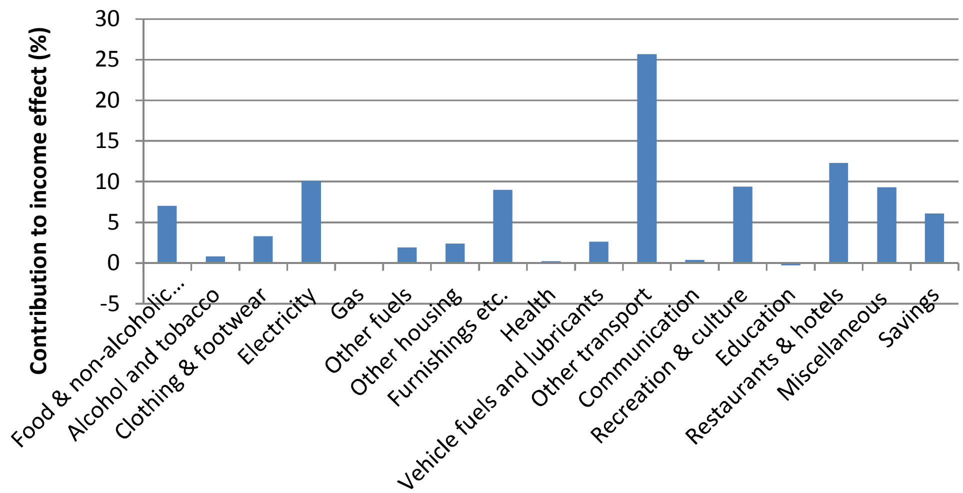


Figure 5 Estimated contribution of different commodity groups to the income effect



7 Results

In this section, we present our estimates of the rebound effects from the different measures averaged over a period of ten years. We present the results in four stages, namely:

- income effects only, ignoring capital costs;
- income and embodied effects, ignoring capital costs;
- income and embodied effects, allowing for capital costs; and
- sensitivity to key variables.

7.1 Income effects only

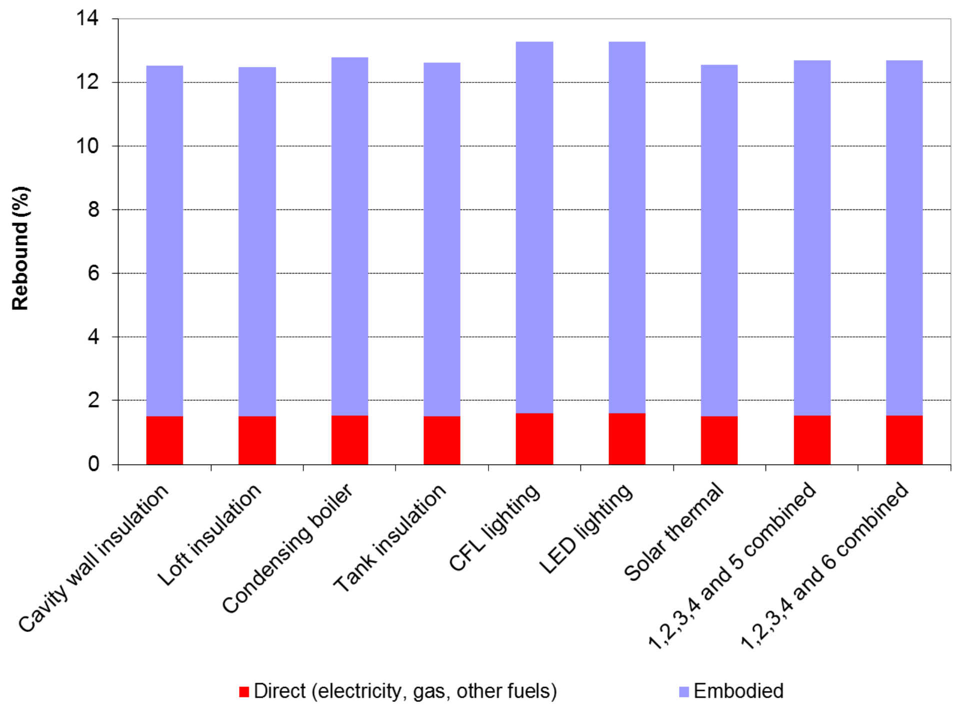
Figure 6 illustrates the estimated rebound effect from income effects alone, ignoring both the embodied effect and the capital cost of the measures. This shows that the estimated rebound effects are <u>modest</u> and broadly comparable across all measures, with a mean of **12.4%** for the heating measures **13.0%** for energy efficient lighting and **12.5%** for the two combinations of measures. These estimates are lower than many in the literature and derive from the fact that the bulk of the cost savings are spent on commodities that have a significantly lower GHG intensity than domestic energy consumption. The difference between the estimated rebound effects for lighting and heating measures is relatively small, implying that both measures save a comparable amount of money for each kg of GHG saved. This is because, in our model, expenditure on electricity is ~80% as GHG intensive as expenditure on natural gas. If rebound effects were to be measured on an energy basis, the difference between the two measures may be larger.

Figure 6 also breaks down the income effect into direct and embodied emissions- where the former relates to increased consumption of energy commodities (electricity, gas and other fuels) and the latter relates to increased consumption of other goods and services. This shows that embodied emissions are substantially more important than direct emissions - with the latter accounting for only 13% of the total.

The estimated rebound effect for energy efficient lighting is influenced by our modelling of the heat replacement effect (i.e. the increased use of heating fuels to compensate for the loss of heat from incandescent bulbs). Heat replacement reduces the engineering effect from energy efficient lighting by proportionately more than the income effect. Hence, when there is no heat replacement, our estimate of the rebound effect for lighting falls to **10%** (implying a 'heat replacement rebound' of around 3%).

Our estimates are comparable with those from earlier studies that used a similar methodology to investigate lighting and heating measures. For example, Druckman *et al* (2011) estimate a 7% rebound effect following adjustment of thermostats by UK households, Murray (2011) estimates a 5% rebound effect following electricity conservation measures by Australian households and Thomas (2011) estimates a 7% rebound effect following improvements in electricity efficiency by US households.

Figure 6 Estimated rebound effects from income effects alone, showing contribution of direct and embodied emissions

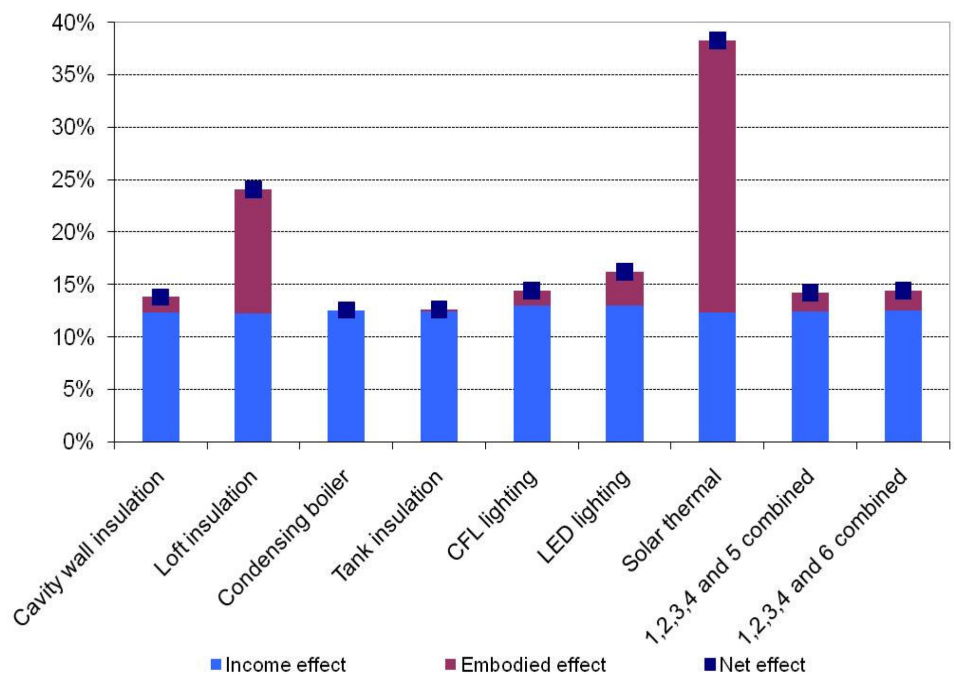


7.2 Allowing for the embodied effect

Figure 7 illustrates how the rebound effect is modified when an allowance is made for the embodied effect. Ignoring capital costs, this leads to a mean rebound effect of 20% for the heating measures (or 16% without solar thermal), 15% for the lighting measures and 14% for the two combinations of measures. The embodied effect is estimated to account for 10% of the rebound effect for cavity wall insulation, 20% for LED lighting, 49% for loft insulation and 67% for solar thermal. This demonstrates that the embodied effect should not be ignored, but is nevertheless relatively modest for all the measures considered. The exception is solar thermal, but even this has an estimated 'GHG payback time'[16] of less than three years. The contribution of the embodied effect to the rebound effect also depends upon the time interval of interest. For example, averaging over five years raises the estimated rebound effect for the two combinations of measures by one percent. However, the most appropriate metric is the full economic lifetime of the relevant measure which in the case of insulation and solar thermal is many decades. Over this period, the engineering savings greatly exceed the embodied emissions of the relevant equipment.

These results treat the embodied effect (ΔM) as offsetting some of the anticipated GHG savings from the measure (ΔH) and thereby contributing to the rebound effect. An alternative approach (Equation 4) is to subtract the embodied effect from the anticipated GHG savings. This reduces the mean rebound effect to 14% for the heating measures (or 13% without solar thermal), and to 13% for both the lighting measures and the two combinations of measures. Once again, this demonstrates that, with the exception of solar thermal, the income effect dominates.

Figure 7 Estimated rebound effects from income and embodied effects, ignoring capital costs



7.3 Allowing for capital costs

Figure 8 illustrates how allowing for capital costs reduces the net cost saving from each measure and hence the estimated rebound effect - leading to a mean rebound effect of 3.4% for the heating measures (or 11% if solar thermal is ignored), 5% for the lighting measures and 11% for the two combinations of measures. With the assumptions used here, both solar thermal and LEDs are estimated to have a simple payback that exceeds ten years and hence are found to have a negative rebound effect over this period. Taking the CERT subsidies into account (Figure 9) leads to higher net cost saving and hence higher rebound effects – respectively **15%** for the heating measures, **9%** for the lighting measures and **14%** for the two combinations of measures.

In practice, only a portion of eligible households will benefit from subsidies and these are currently funded through higher energy bills for all household consumers (Sorrell et al., 2009c). For example, DECC (2010c) estimates that CERT raised household gas prices by 2.8% in 2010 and household electricity prices by 3.3%. These energy price increases will reduce real household incomes and expenditures and hence reduce both energy-related and total GHG emissions. As a result, the positive income effect from the energy efficiency improvements will be offset by a negative income effect from the energy price rises - for both participants and non-participants in CERT (Sorrell et al., 2009c). To properly account for this, it would be necessary to estimate the proportional contribution of each measure to the overall increase in energy prices.

These estimates also assume implementation of the EU Directive on energy efficient lighting. If instead, we assume that incandescent bulbs continued to be available, the embodied effect of energy efficient lighting would be lower (since the emissions embodied in subsequent purchases of incandescent bulbs would be avoided), but the income effect would be higher (since the cost of those purchases would be avoided too). The net effect is to raise the average rebound effect for lighting from 9% to 14%.

Figure 8 Estimated rebound effects from income and embodied effects, with full capital costs

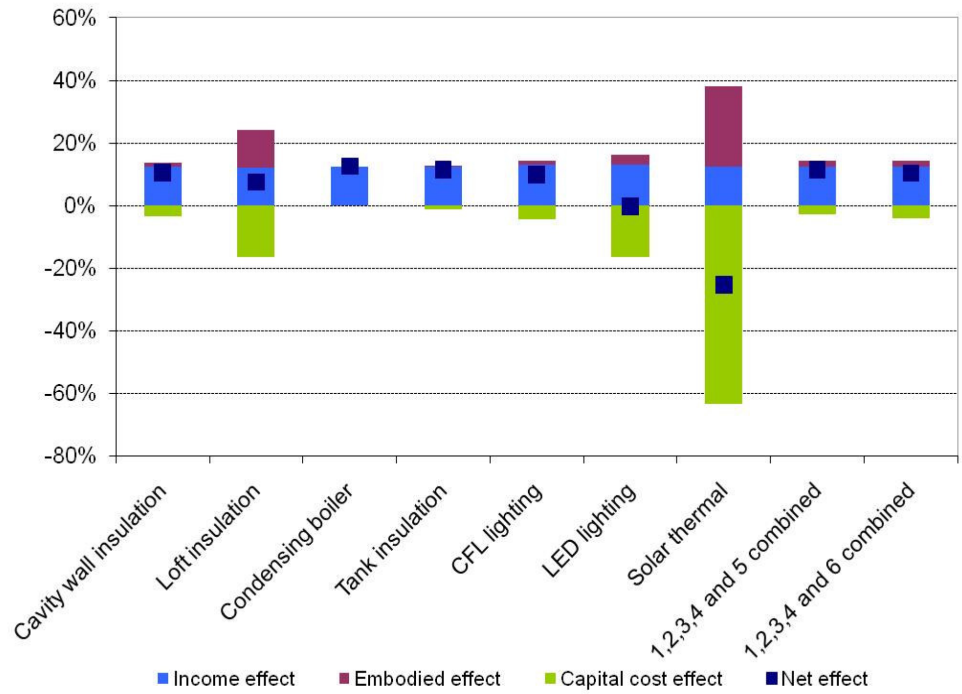
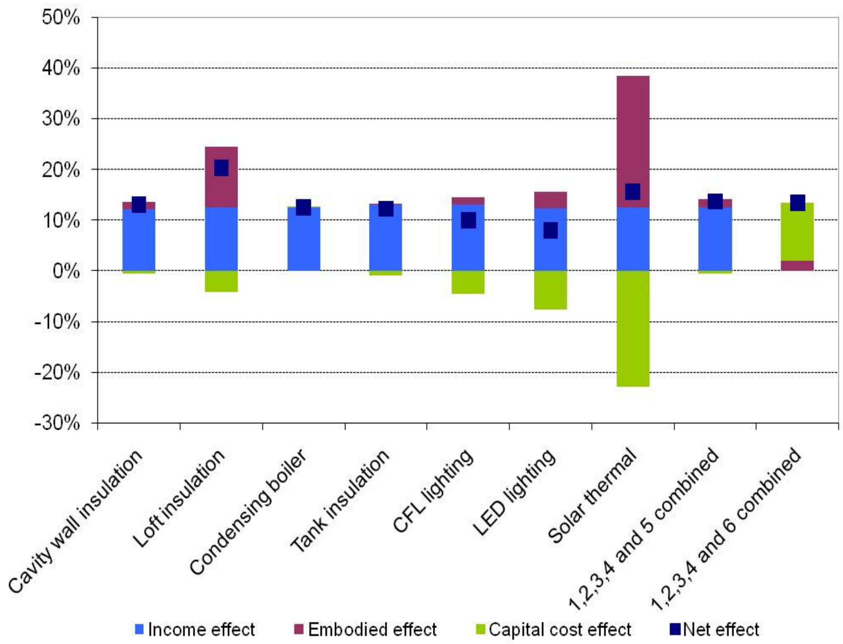


Figure 9 *Estimated rebound effects from income and embodied effects, with subsidised capital costs*



7.4 Sensitivity to assumed elasticities

Our results suggest that heating measures have a near-zero direct rebound effect, owing to our assumption that gas has an income elasticity of zero.[17] But a growing literature finds direct rebound effects of 10-30% for heating measures, with significantly larger effects for households on low incomes (Sorrell et al., 2009a). Most of these studies capture both income and substitution effects, while our estimates are confined to the latter.[18] To explore this further, we re-estimated the results assuming an income elasticity of 0.9 for gas consumption (much higher than encountered in practice). This increased the estimated rebound effect for the heating measures from 14.7% to 16.4%, and that for the combination of measures from 13.5% to 16.5%. The overall rebound effect therefore appears relatively insensitive to assumed income elasticity of gas consumption, owing to the small share of gas in total expenditure. This suggests that the direct rebound effect for household heating may derive in large part from substitution effects, although the income effect will be greater for fuel poor households.

For comparison, we repeated the analysis with different assumptions for the income elasticity of the 'other transport' category, which is the largest contributor to the income effect. Varying this from 0.1 to 0.9 changed the rebound effect for all measures combined from 12.6% to 14.6% - implying again that the results are relatively insensitive to the assumed income elasticities

7.5 Sensitivity to the GHG intensity of electricity use

The above estimates hold all relevant variables fixed over the ten-year period, but changes in any of these variables will affect the results. Of particular interest are future changes in the GHG intensity of electricity consumption (in kgCO_2e/kWh), since this is anticipated to fall to ~55% of current levels by 2020 and ~10% of current levels by 2030 (CCC, 2008). These changes will reduce the GHG savings from electricity efficiency improvements (ΔH), while having a much smaller impact on the GHG emissions from re-spending (ΔM). Repeating the analysis[19] for energy efficient lighting, we find that: a 45% reduction in the GHG intensity of electricity expenditure (in kgCO_2e/£) leads to a rebound effect of **24%**; a 60% reduction leads to a rebound effect of **54%**; and a 90% reduction leads to a negative rebound effect. The last result derives from the heat replacement effect, with the GHG savings from reduced electricity consumption being more than offset by increased emissions from heating fuels. Since incandescent bulbs will soon be eliminated, it is more insightful to model the rebound effect without heat replacement. This leads to an estimated rebound effect of **98%,** implying virtually no GHG savings and a high risk of backfire.

In these scenarios, energy efficient lighting reduces consumption of low carbon electricity but frees-up money to be spent on other goods and services whose GHG intensity is held fixed.

The calculations therefore overestimate the rebound effect from such measures, since a shift to low carbon electricity would reduce the GHG intensity of other goods and services as well and thereby lower the embodied and income effects. However, the embodied and income effects will not reduce as much as the engineering effect because: first, electricity only accounts for a portion of the relevant emissions; second, at least 40% of embodied GHG emissions originate from countries outside the UK (including China), many of whom will much make slower progress than the UK in reducing the GHG intensity of their manufacturing industries (Druckman and Jackson, 2008); and third, rising electricity prices should increase the cost savings from efficiency improvements which in turn will increase the associated income effects. As a result, the rebound effect (in GHG terms) from electricity efficiency measures may be expected to increase significantly in the period to 2030.

It should also be noted that UK electricity generators are participating in the EU emissions trading scheme (EU ETS) and hence are covered by an EU wide carbon cap. In this context, any actions that reduce carbon emissions from UK electricity generators, including improvements in household electricity efficiency, will not reduce global carbon emissions at all. This is because such actions will simply free up allowances that could be used by other participants in the EU ETS to cover either increases in emissions or reduced emissions abatement (Sorrell and Sijm, 2003). Alternatively, the allowances may be banked and used in subsequent trading periods, but they will still ultimately be used to cover emissions. Hence, from this perspective, the engineering effect of electricity efficiency improvements is *zero* while the EU ETS cap is in place. As a result, improvements in electricity efficiency will *increase* aggregate GHG emissions as a consequence of the embodied and income effects.[20]

However, this observation does not imply there is no justification for encouraging improved electricity efficiency through measures such as CERT. Such improvements may deliver longer term, environmental benefits,[21] as well as contributing to other policy objectives such as tackling fuel poverty. Also, by addressing the market failures inhibiting such investment, such policies can encourage a more cost-effective means of delivering electricity services than increasing electricity supply.

8 Summary

This study has estimated the combined direct and indirect rebound effects from seven measures that improve the energy efficiency of UK dwellings. Five of these measures target heating energy consumption, two of them target electricity consumption and four are eligible for investment subsidies. The rebound effects were measured in GHG terms, including both direct and embodied emissions and relate to an average UK household. The effects were averaged over a period of ten years.

Our main finding is that the rebound effects from these measures are in the range **5-15%**, depending upon the time period examined and assumptions used. The primary source of these rebound effects is the re-spending of the cost savings on non-energy goods and services, and the primary reason the estimated effects are modest is that these goods and services are much less GHG intensive than energy consumption itself. Studies that have investigated measures in less GHG-intensive areas, such as vehicle travel and food consumption, have typically found larger rebound effects.

Unlike other studies, our results explicitly allow for the embodied emissions of the energy efficiency measures themselves. In most cases these were found to contribute a relatively small proportion (~15%) of the total rebound effect. However, there were exceptions (notably solar thermal) and the contribution of the embodied effect depends upon the time period examined.

Direct rebound effects, such as increased consumption of heat following insulation improvements, were found to be much smaller than indirect effects, owing largely to the small share of energy in total household expenditure. However, as with most studies published to date, our methodology only captures the income effects from energy efficiency improvements and not the substitution effects. These could either add to or offset the income effects for both energy commodities and other goods and services and therefore lead to either a higher or lower rebound effect. In practice, we would expect most substitution to be *towards* the (now cheaper) energy services and *away* from other goods and services. Since the former are more GHG intensive than the latter, the net result, should be to *increase* the rebound effect. Hence, since our methodology neglects this mechanism, it is likely to underestimate rebound effects. Our methodology also neglects any responses on the production side of the economy, the net result of which could also be to increase economy wide rebound effects.

The estimated rebound effect from improvements in electricity efficiency is sensitive to the GHG intensity of electricity expenditure. A transition to a low carbon generating system will increase the rebound effect (in GHG terms) from such measures and ultimately create the risk of backfire - with an increasing portion of these emissions occurring overseas. Moreover, since emissions from UK electricity generators are capped by the EU ETS, such measures effectively lead to backfire already. This counter-intuitive observation demonstrates the importance of measures such as border carbon adjustments to discourage this type of carbon leakage.

Our approach could be improved in a number of ways. For example, confining attention to an 'average' household precludes the investigation of how rebound effects vary between different socio-economic groups; using only 16 commodity groups overlooks the wide disparities in GHG intensity between commodities *within* each group; and the use of a static, I-O framework precludes the investigation of broader, economy-wide adjustments in prices and incomes. Further research should seek as far as possible to address these limitations and to establish the conditions under which rebound effects may be larger or smaller. However, trade-offs must always be made: for example, using a greater level of commodity disaggregation would make it harder to estimate substitution effects, since it is more difficult to obtain the required cross-price elasticity estimates. This suggests the need for multiple studies, offering complementary perspectives on this important phenomenon.

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Annex 1 -Decomposing rebound effects into income and substitution effects

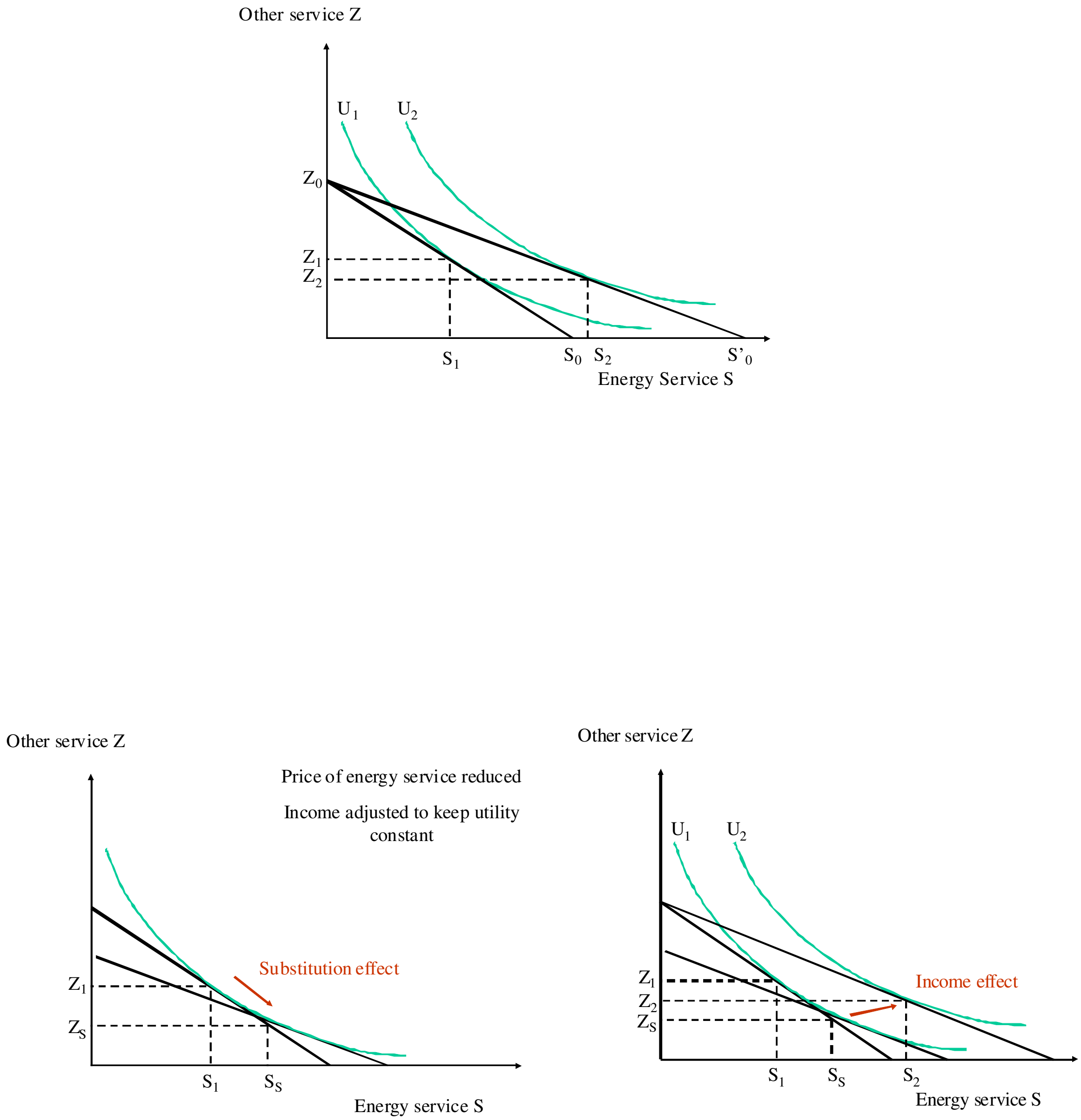
For energy efficiency improvements, it is the reduction in the effective price of the energy service (e.g. the lower cost per mile) that drives the rebound effect. It is common practice to break down the behavioural response to this price reduction into an *income* effect and a *substitution* effect. This relies on the notion that households obtain *utility* from consuming goods and services and that they seek to maximise this utility. This breakdown is theoretical in that only the sum of the two effects is observed, but the income and substitution effects can be estimated statistically using standard techniques. Both the direct and indirect rebound effects can be broken down in this way. Energy efficiency improvements lead to both income and substitution effects, while behavioural changes only lead to income effects.

The difference between income and substitution effects is illustrated in Figure A.1. This shows the theoretical trade-off between consumption of an energy service (S) by a household and consumption of another good or service (Z). Consumers are assumed to maximise their 'utility' (U) subject to a budget constraint. At one extreme, the consumer could choose to consume S_0 of the energy service and none of Z, while at the other extreme she could consume Z_0 of the other service and none of the energy service. Prior to the energy efficiency improvement, the optimum mix is given by (S_1, Z_1), where the budget constraint is tangential to the indifference curve U_1. At this point, utility is maximised. An energy efficiency improvement reduces the effective price of the energy service (S) and allows greater consumption of both this and the other service (Z). The optimum mix is now given by (S_2, Z_2) where the new budget constraint is tangential to the indifference curve U_2 which represents the maximum amount of utility that can be obtained from the new level of 'real income' (money income is unchanged). Hence, consumption of the energy service increases ($S_2>S_1$), consumption of the other commodity reduces ($Z_2<Z_1$) and the consumer obtains a higher level of utility ($U_2>U_1$).

Figure A.2 also shows how the change in the mix of commodities consumed can be broken down into a substitution effect and an income effect. The *substitution effect* is defined as the change in consumption that would result from the change in relative prices *if* money income were adjusted to keep utility constant. In effect, the change in consumption is artificially restricted to a movement along the original indifference curve. But since the energy service has become cheaper, the consumer's total purchasing power, or 'real income' has increased. This allows a shift from one indifference curve to another. The *income effect* is defined as the change in consumption that would result exclusively from this change in real income, holding other prices and money income constant. Standard techniques in microeconomics (the Slutsky equation) allow the two effects to be individually identified. Note that, in this case, the substitution (S_S-S_1) and income (S_2-S_S) effects for the energy service have the same sign and hence *reinforce* one another while the substitution ($Z_s<Z_1$), and income ($Z_2>Z_S$) effects for the other service have different signs and hence *offset* one another.

To estimate income effects, it is necessary to have estimates of the GHG intensity and expenditure elasticity of different categories of household goods and services. To estimate substitution effects, it is necessary, in addition, to have estimates of the own-price and cross-price elasticities of different categories of goods and services. Empirical methods that use cross-sectional (i.e. single year) data on household expenditure are only able to estimate income effects since there is little variation in prices within a single year. In contrast, empirical methods that use either time series or pooled cross-sectional (i.e. multi-year) data on household expenditure can estimate both income and substitution effects, since there is significant variation in prices from year to year.

Figure A.1 Illustration of income and substitution effects



Annex 2 Assumptions for solar thermal heating

We assume an average annual heat generation from solar panels of 500 kWh/m2 and an average area of 3.5 m^2 (DECC, 2010e) which leads to an assumed heat generation of ~1750 kWh/year from each panel. The associated carbon and cost savings depend upon the fuel mix for water heating. Using (DECC, 2002) we assume 82.5% gas, 9.4% oil, 2.6% solid fuels and 5.5% electricity. Using the conversion factors in Table 6, this leads to estimated GHG savings for an eligible dwelling of 454 $kgCO_2e$/year (6.4%) and cost savings of £67/year (6.1%).

We estimate that a maximum of 40% of UK dwellings have viable roof space for solar thermal heating, together with space for the hot water cylinder. Averaging over the whole dwelling stock, this leads to potential energy saving for an 'average' dwelling of 700 kWh/year (2.6%), GHG savings of 182 $kgCO_2e$/year (3.1%) and cost savings of £27/year (2.5%).

The incentive payments proposed by the UK Renewable Heat Incentive (DECC, 2010f) could transform the economics of solar thermal heating, but these are excluded from the present analysis since the level of payments had not been finalised at the time of writing.

Annex 3 – Assumptions for the embodied GHGs of energy efficiency measures

- *Cavity wall insulation*: We estimate that individual dwellings eligible for cavity wall insulation have a mean net wall area (after subtracting glazing and door areas) of 67.3m^2 and a mean cavity width of 65 mm (Firth et al., 2009). This gives 4.37m^3 of cavity which is assumed to be filled with mineral wool of density 25 kg/m^3 and embodied GHGs of 1.28kgCO_2e/kg (Hammond and Jones, 2011), leading to 140 kgCO_2e of embodied GHGs for an eligible dwelling. Assuming 39.4% of dwellings are eligible for cavity wall insulation, this leads to an estimate of **55.2 kgCO_2e** of embodied GHGs for an average dwelling.

- *Loft insulation:* We estimate that individual dwellings eligible for top-up loft insulation have a mean roof area of 45 m² and a mean thickness of existing insulation of 0.149m (Firth et al., 2009; Johnston, 2003). Topping up existing insulation to 270 mm is assumed to require 5.45m^3 of mineral wool of density 25 kg/m^3 and embodied GHGs of 1.28kgCO_2e/kg (Hammond and Jones, 2011), leading to 174 kgCO_2e of embodied GHGs for an eligible dwelling. Assuming 67.9 of dwellings are eligible for top-up insulation,[22] this leads to an estimate of **118.3 kgCO_2e** of embodied GHGs for an average dwelling.

- *Condensing boiler*: We could find no reliable information on the embodied GHGs of a condensing boiler relative to a less efficient alternative. More importantly, it is no longer possible to purchase an inefficient boiler in the UK, since all new boilers fitted from April 2005 must be 'A' or 'B' efficiency rated with a first law efficiency of 86% or more. Approximately one fifth of the existing boiler stock is condensing (Firth et al., 2009), but the premature replacement of an existing boiler before the end of its natural life is unlikely to be economic.[23] We therefore assume the natural replacement of existing boilers at the end of their life and assume that the incremental embodied GHGs are zero.

- *Tank insulation:* We assume the replacement of the existing insulation jacket with a new jacket of standard size for a domestic boiler (1050 x 45 0 x 80 mm) and weight 1.7 kg. We assume the insulation material is fibreglass with embodied GHGs of 1.3 $kgCO_2e/kg$, ignore all other materials and assume that all dwellings are eligible. This leads to an estimate of **2.3 $kgCO_2e$** for the embodied GHGs of an average dwelling.

- *Compact fluorescents:* We assume an average of 24 light fittings per dwelling and an average load factor of 6% (Frondel and Lohmann, 2011; Peacock and Newborough, 2004).[24] Using standard estimates of bulb lifetime (Osram, 2009), this implies an average lifetime of 2 years (1000 hours) for a standard incandescent bulb and 20 years (10000 hours) for a CFL. But common switching patterns have been shown to shorten CFL lifetimes (Jump et al., 2008), so we consider that a lifetime of 11 years (6000 hours) is more realistic. In either case, this implies that CFLs installed now should last at least ten years, which is the longest time period we consider for an estimate of rebound effects (T=10). We further assume that 40% of existing lighting is CFLs and that none of these bulbs will need to be replaced over the next ten years. Hence, over a ten-year period, we assume that the premature replacement of inefficient lighting in an average dwelling will require the purchase of 14.4 CFL bulbs and will avoid the purchase of 120 incandescent bulbs. Osram (Osram, 2009) estimate that a single incandescent bulb has embodied emissions of 0.14 $kgCO_2e$ while the corresponding figure for a CFL is 0.88 $kgCO_2e$. Combining these assumptions leads to an estimate that, averaged over a period of 10 years (T=10), prematurely replacing incandescent with CFLs in an average dwelling will lead to incremental embodied GHGs of **2.59 $kgCO_2e$**. But these calculations ignore the

EU legislation requiring the progressive phasing out of incandescent bulbs in the period up to September 2016. Allowing for this legislation lowers the embodied emissions of the counterfactual scenario and leads to a higher estimate of **12.7 kgCO2e**.

- *LED lighting:* We use a similar set of assumptions for estimating the incremental embodied emissions of prematurely replacing all existing lighting with LEDs, averaged over a period of 10 years. From (Osram, 2009), we assume that a single LED bulb has embodied emissions of 2.4 kgCO_2e and a lifetime of up to 47 years at 6 load factor. If we further assume that 40% of existing lighting is CFLs and these bulbs would have lasted ten years, then the purchase of 24 LEDs now will avoid the purchase of 120 incandescent bulbs over the next ten years. Combining these assumptions leads to an estimate that, averaged over a period of 10 years (T=10), prematurely replacing all existing lighting with LEDs in an average dwelling will lead to incremental embodied GHGs of **24.5 kgCO_2e**. But again, these calculations ignore the EU legislation requiring the progressive phasing out of incandescent bulbs. Allowing for this leads to a higher estimate of **34.6 kgCO2e**.

- *Solar thermal:* Menzies (2010) provides LCA estimates for the embodied carbon of three 2.03m^2 flat plate collectors, including cylinder, pipework, manufacturing, transport, installation and maintenance. This leads to an estimate of the embodied carbon for the total system of 1439 kgCO_2. But this figure cannot be simply scaled to our 3.5m^2 panel since the embodied carbon of items such as the cylinder is independent of panel size. Using the figures in Tables 2-9 in Menzies (2010), we estimate the embodied carbon of each component of a 3.5 m^2 system, leading to a total figure of 1068 kgCO_2. Assuming further that only 40% of dwellings are eligible for solar thermal, this leads to an estimate of **427 $kgCO_2e$** for the embodied GHGs of retrofitting solar panels to an average dwelling – which is substantially higher than the estimates for all the other measures combined.

Endnotes

[1] By natural replacement, we mean the replacement of equipment that has come to the end of its economic life. By premature replacement, we mean replacement of equipment that has not reached the end of its economic life.

[2] Solar thermal heating is unlikely to be cost effective without subsidies.

[3] These savings are a function of the number of eligible dwellings, their structure, composition and thermal integrity, the energy efficiency of the relevant conversion equipment and the effectiveness of the measure compared to the relevant alternative.

[4] The framework can accommodate multi-year loan repayments if required.

[5] We assume a value of 7.8% for r which is the estimated UK saving ratio for 2009 (www.ons.gov.uk). The mean over the period 2000-10 was 4.7%.

[6] An alternative is to treat savings as deferred consumption that will lead to GHG emissions at a later date. In this case, the environmental impact will depend upon future trends in incomes, interest rates, inflation rates, relative prices, consumption patterns and the GHG intensity of different goods and services.

[7] Investment includes: gross fixed capital formation + changes in inventories + acquisitions less disposals of valuables .

[8] Based upon data from the 2008 English Housing Survey.

[9] The rate of fabric and ventilation heat loss in steady-state conditions

[10] We use the long-run income elasticity, since we are estimating rebound effects over an extended period of time with other variables held fixed.

[11] SELMA is a general framework that can be applied to, for example, resource use (such as energy use), carbon dioxide emissions or GHGs. In this study we use the Kyoto basket of six GHGs: carbon dioxide, methane, nitrous oxide, hydro-fluorocarbons, perfluorocarbons and sulphur hexafluoride. These are estimated in units of carbon dioxide equivalent (CO_2e) using the conversion factors specified in the UK Environmental Accounts.

The choice of conversion factor depends upon the time frame of interest and the use of different time periods can lead to different conclusions regarding the relative global warming potential of different gases.

[12] Note that embodied emissions are being referred to here, not the embodied component of the rebound effect (ΔM))

[13] UK emissions are measured here from a 'production' perspective which ignores emissions from aviation and shipping and those embodied in traded goods, while a households' GHG footprint is measured from a 'consumption' perspective which includes the above categories of emissions.

[14] Defined as 21-23^{o}C in the living areas and 18^{o}C elsewhere. The definition is based on modelling estimates of required rather than actual expenditures and relates to all forms of energy, rather than heating fuels alone.

[15] The elasticity estimate for natural gas should be treated with caution since the gas expenditure estimation in ELESA is not completely satisfactory. A number of different experiments were undertaken and the equation used here was the 'best' [8] that could be obtained.

[16] The ratio of embodied GHG emissions to annual GHG savings.

[17] We still estimate a small direct rebound effect for heating, since a proportion of heating energy derives from electricity and other fuels which are assumed to have a non-zero income elasticity.

[18] These studies use a mix of (quasi-)experimental studies of efficiency improvements and econometric estimates of the own-price elasticity of heating demand, or various proxies for heating demand (Sommerville and Sorrell, 2007; Sorrell, 2007; Sorrell and Dimitropoulos, 2007; Sorrell et al., 2009b). Most estimate rebound effects in energy, rather than GHG terms.

[19] In this sensitivity analysis we reduce the GHG intensity of direct electricity use but leave the GHG intensities of other goods and services unchanged.

[20] More specifically, emissions will be increased by the proportion of the embodied and income effects that is not covered by the EU ETS cap.

[21] This argument is valid for the period to 2020 - the end of EU ETS Phase 3. Beyond Phase 3, it is expected that the EU ETS cap will be tightened and/or the policy framework modified. Hence, the effect of measures to improve electricity efficiency on GHG emissions after 2020 will depend upon whether and how these measures influence the EU-wide policy mix after that date (including the stringency of any post-2020 EU ETS cap), together with the stringency of the international climate policy regime. To the extent that such measures contribute to lower and declining UK emissions they may help the UK in negotiating more stringent emission reduction targets, both within the EU and internationally and thereby contribute to global carbon abatement in the long-term.

[22] In 2007, DECC (2010e) estimated that 24.8% of GB dwellings had <100 mm insulation, 32.7% between 100 and 150mm and 32.4% with >150 mm. For the same year, Firth *et al* (2009) estimate a roof U-value for average English dwelling of 0.4 W/m^2. Ofgem (2008 p. 48) estimate typical U-values for an un-insulated roof of 2.3 W/m^2K. This falls to 0.707 W/m^2K with 50 mm insulation; 0.494 W/m^2K with 100 mm; 0.387 W/m^2K with 150 mm; 0.228 W/m^2K with 200 mm: and 0.185 W/m^2K with 270 mm.

[23] We estimate that premature replacement of an F-rated boiler would give a payback of 18 years, with longer paybacks for replacement of C or D rated boilers. Premature replacement of a G-rated boiler (<70% efficient) may be economic, since this is eligible for CERT subsidies of up to 100%. G-rated boilers were installed before 1997 when UK building regulations first required a minimum thermal efficiency of 70% for new boilers. We estimate that approximately 37% of the 2009 English boiler stock was installed before that date.

[24] Background work for 40% house project suggests an average UK house using 100% incandescent bulbs had an annual lighting load of 731kWh (Peacock and Newborough, 2004). Assuming the house has 24 60W lightbulbs, this implies an average load factor for each bulb of **6%** (1.5 hours a day). For comparison, Frondel and Lohmann (2011) report an average load factor of 8.3% (2 hours/day) for lighting in a typical 3-4 person household and note that load factors will be lower in a single two-person household.